EFA for Structure Detection in Image Data

Empirical Results on Two Datasets of Different Perspective

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***Abstract*—Structure detection discovery from image data is scarce. Hence, we attempt to explore and uncover the underlying structure from two datasets of different perspective through statistical procedures commonly used in psychology, social science, health and business. Firstly, distinction between principal component analysis and exploratory factor analysis are briefly described; along with a simple test on the growth of publications on both techniques and datasets tested in this paper. Exploratory factor analyses results with and without data screening are summarized. 3-factor structures are derived from both datasets where texture features seem to be dominant than others. Some critical issues concerning the appropriateness of methods are also discussed. The systematic procedures described in this paper are applicable to any other object type with similar characteristics as the ones tested.**

Keywords—structure detection; exploratory factor analysis; factor loadings; homogeneous; common variance

I. INTRODUCTION

Many publicly available image databases used for visual object detection and categorization benchmarks in computer vision researches [1], [2], [3], [4], [5] tend to be homogeneous and formed single perspective under controlled environments. Therefore, most works tend to predetermine unique features customized to specific problem [6], [7], [8]. These customized features are difficult to replicate for other problems and limited in descriptive power. Therefore, both the need to explore and uncover common aspects of an object for semantic characteristics regardless of occlusion and orientation variation are crucial. The importance of symbolic-level abstraction was highlighted in a layered architecture [9]. The common aspects of object or abstraction are derived through grouping and description on the relationships between visual features using exploratory factor analysis (EFA).

II. RELATED WORKS

One of the most confusing and misunderstood issues in statistical teaching and practical literature is the difference between principal component analysis (PCA) and EFA. EFA and PCA are sometimes treated as synonymous techniques which have been criticized [10], [11], [12]. PCA is a data reduction technique which maximizes the amount of variance accounted for in the observed variables by a smaller set of variables called principal components. EFA is a model based technique, typically used when the goal is unknown structure detection for a grouped of measured variables. Confusion between PCA and EFA is due to the grouping of PCA under the heading of factor analysis in statistical software package, SPSS [13].

PCA and EFA have grown tremendously in terms of paper published. To validate the growth in publication, a simple test is conducted by searching the terms “Principal Component Analysis” or PCA and “Factor Analysis” or FA in two major digital libraries from year 2010 to 2015. Publications on EFA range from 0.500% (IEEE) to 4.811% (ACM) as compared to publications on PCA. Fields of publications varied among networking, security, management, technology, medicine, biology, computing, database, education. The severe difference in publication count may as well due to PCA being frequently (and mistakenly) considered to be a form of factor analysis [14].

This paper describes the systematic procedure for modeling the relationship between variables via EFA. There are vast literatures available for the step-by-step guide on EFA [15], [16], [17], [18] and will not be cover in this paper. Remainder of this paper is structured as followed: datasets and image features are briefly described in section III, followed by EFA with and without data screening in section IV. Analyses results are discussed in Section V. Finally, conclusion and future works are given in section VI.

III. DATA COLLECTION

A. Image Datasets

Quick reviews on the aforementioned databases led to testing on LabelMe database [4] where images came from a wide variety of sources and initially not posed for research. Therefore, images were shot in different angles; some with complete objects while other with occluded objects and noisy annotations by public. A subset of 292 images annotated as “butterfly” is extracted as dataset A (refer Fig.1). Occluded objects are included so the dataset is as close to real-life application as possible instead of using all perfectly complete objects.

In contrast to dataset A, images in dataset B are perfectly complete objects. Dataset B is formed by approximately 593 butterfly images extracted from scanned version of an entomology book [19]. Hence, objects are prepared in standard spreading and captured indoor with standard lighting